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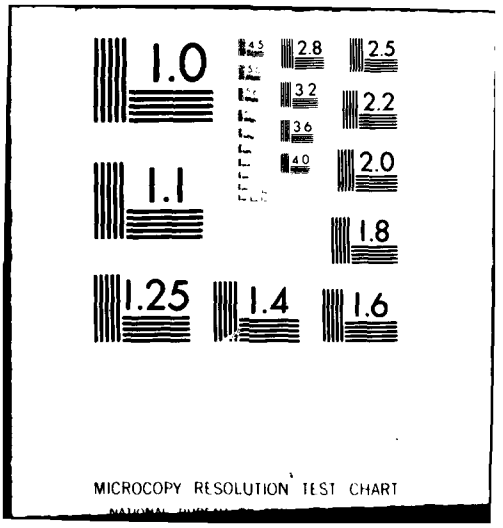
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A PRELIMINARY REPORT ON A MULTI-LEVEL LEARNING TECHNIQUE USING PRODUCTION SYSTEMS*

BY

NICHOLAS V. FINDLER

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20. ABSTRACT (Continue on reverse side if necessary and identify by block number)

A generalized production system is described. The rules in it connect causally and stochastically related open and hidden variables. An open variable can be observed and measured at any time whereas the values of a hidden variable can be identified only at certain times. Both the causes and effects can be either open or hidden variables. The objective of the system is to provide sharper and sharper estimates of the values of hidden variables. A multi-level learning mechanism is outlined that leads to better and larger knowledge bases.

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A PRELIMINARY REPORT

ON A MULTI-LEVEL LEARNING TECHNIQUE

USING PRODUCTION SYSTEMS

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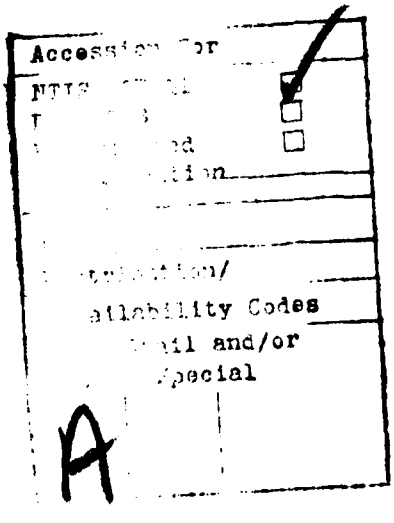
State University of New York at Buffalo



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ABSTRACT

A Generalized Production System, which is under development, is described. The rules in it connect causally and stochastically related open and hidden variables. An open variable can be observed and measured at any time whereas the values of a hidden variable can be identified only at certain times. Both the causes and effects can be either open or hidden variables. The objective of the system is to provide sharper and sharper estimates of the values of hidden variables. A multi-level learning mechanism is outlined that leads to better and larger knowledge bases.

INTRODUCTION

Whereas the speed and accuracy of computers surpass the capabilities of man by a large factor, the power and flexibility in human problem-solving and decision-making represent a continuing challenge to researchers in A.I. A group of students and the author have been engaged in a long-term investigation on decision-making, judgment and choice under uncertainty and risk. (See, e.g., [1-10].) One of the larger subprojects within this framework aims at a system which would establish rules of pattern formation, recognize stochastic relations between patterns of causally related variables, and use such relations as part of an evolving strategy.

The system, under development, will be relatively context-independent. Its main components, as shown on Figure 1, are: the Pattern Identifier and Categorizer (PIC), the Generalized Production System (GPS -- sorry about the acronym), the Symbolic Transcriber (ST), and the Learning Strategy (LS).

The last component and, of course, the Competitive Environment are fully context-dependent.

- -

FIGURES 1 AND 2 ABOUT HERE

- -

THE GENERALIZED PRODUCTION SYSTEM

The main subject matter of this paper is the GPS component. The role of the other parts will be outlined only briefly as most of it is discussed elsewhere.

The Competitive Environment provides along the time scale sample values of certain variables for PIC. Some of these are open variables which can be observed and measured (possibly with some error) by the participating strategies at any time. Some others are hidden variables whose values can be identified only at certain times when the competitors (must) display them publicly. The open and hidden variables are causally and stochastically related to each other in any given strategy -- both causes and effects can be either open or hidden variables.

PIC fits a minimum number of basic patterns, which we call morphs, to the time-sequence of open variable values [11, 12]. The morphs can be trends (monotonic increases or decreases), "sudden changes" of momentary effect, step functions, and delay functions (spanning over a time period during which the mathematical description of the event sequence is not possible with the given "tool kit"). This is shown in a parametric form on Figure 2.

Before we discuss GPS, a few introductory words about Production Systems (PS) may be in order. As is well-known to the

readers, over the past few years PSs have become widely used, both as a technique of programming and as an explicatory mechanism, in cognitive psychology [13] and in A.I. (See the excellent contributions to and the extensive bibliography in [14].) A PS consists of a set of production rules, condition → action pairs. The left-hand side, comprising zero or more condition elements, are templates. When they match an element in the working memory, the production is said to be instantiated. At that moment, the right-hand side, containing one or more action elements, is executed. The actions may make assertions, modify data -- including other production rules -- or the environment itself.

This is not the place to discuss the many issues related to PSs but one important question needs to be mentioned. There can be several production rules whose conditions are matched simultaneously due to ambiguity and uncertainty in the database and/or condition patterns. These rules constitute the so-called conflict set. The selection can be based on priority ordering of the rules or of the elements in the database; on preference of special cases over general ones; on chronological recency of rules (either the most recently executed or the most recently asserted may be selected); and on other criteria. In our system, a quantified level of credibility serves as the basis of such judgment, as explained below.

We want to use the GPS component in our system to obtain a sharp estimate of the current value of any hidden variable. The underlying assumption is that the chronologically preceding sequence of certain datapoints representing observable variables

-- and the morphs fitted through them -- are causally and stochastically related to the value sought. We propose the following formalism

$$M_1/T_1 - H_1 \quad :C_1$$
$$M_2/T_2 - H_2 \quad :C_2$$
$$\cdot \quad \cdot$$
$$\cdot \quad \cdot$$
$$\cdot \quad \cdot$$

Here M_i is the i-th morph fitted; T_j is the j-th timelag between start of the morph in question and the time point at which the hidden variable assumes the value sought (it can be positive or negative, depending on whether the event described by the morph is the cause or the effect of the hidden variable); H_k is the k-th hidden variable value; and C_ℓ is the credibility level of the ℓ-th rule. This "credibility level" is a function of two factors. The first is the extent of noise tolerated in the derivation of the morph with the current sequence of datapoints. The second factor is the degree of consistency in the co-occurrence of the event sequence in question and the hidden variable value over all past experiences in the course of which the -th production rule at hand was established and sharpened. (I note parenthetically that there are several statistics that can be used for the two factors separately -- to estimate the goodness of fit and the extent of "relatedness", respectively. Which ones to employ and how to combine them requires experimentation and may well depend on the nature of the data analyzed.)

The generalized production rules are ordered -- the top one

has the highest credibility level and the rest are in decreasing order. Therefore, there is no need to consider the whole conflict set. The program looks at those rules, one after the other, the right-hand side of which references the hidden variable sought and tries to find a match between its left-hand side and the morphs characterizing the current event sequence. The first acceptable match yields the value wanted. It is to be noted that, in general, a given morph may be related to values of several hidden variables and vice versa. The concept of (assumed) causality does not preclude this phenomenon.

Before we discuss the learning processes applicable with the GPS, a few words should be said about the ST component of the system. This is an extra module planned whose invocation may be appropriate in certain task environments. One would expect the knowledge base of humans to consist of mostly symbolic and qualitative information, possibly reinforced by some simple calculations which are performed inexpensively in terms of time and memory load. It would, therefore, seem appropriate to translate the numerically-oriented language of morphs, time lags, hidden variable values and credibility levels into a symbolic language. The dictionary of this symbolic language needs to consist of only a few syntactic categories -- such as classes of types and sizes -- and a small number of relations between them. The translated version of the generalized production rule, rather than the numerically-oriented one, would then provide the control information for the Competitive Strategy if and when the quality and speed of decision-making improve through it.

Finally, a multi-level learning process is outlined. The

first level is the acquisition of more knowledge -- as the environment sends more events to PIC, more production rules are generated. Second, the credibility levels change -- some increase as further evidence reinforces the correctness of certain rules and some decrease because certain rules may have been generated on the basis of chance co-occurrences. Accordingly, the hierarchy of production rules is continually modified until a steady ordering is reached. The third level of learning concerns the interpreting ability of the ST component. As experience accumulates, the quality of rule translation improves. The fourth level is with reference to the higher performance of the Competitive Strategy relying on a better and larger knowledge base.

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Ernesto Morgado has participated in the design of PIC and has carried out its implementation. The work was supported by AFOSR Grant 81-0220.

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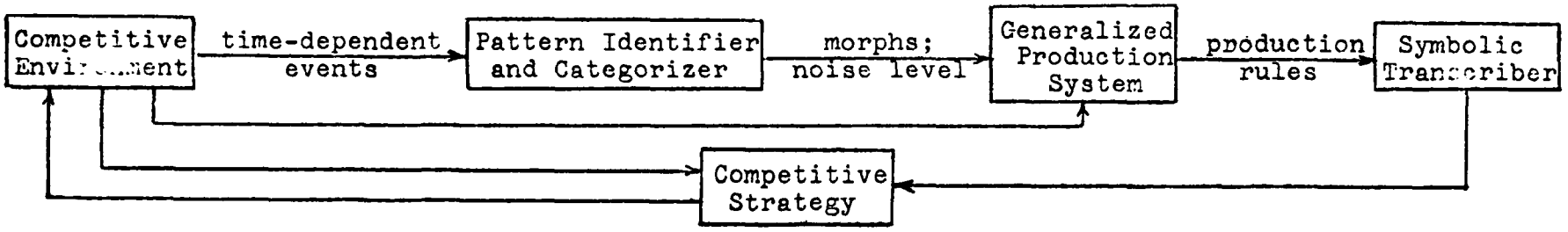

FIGURE 1

System Block Diagram

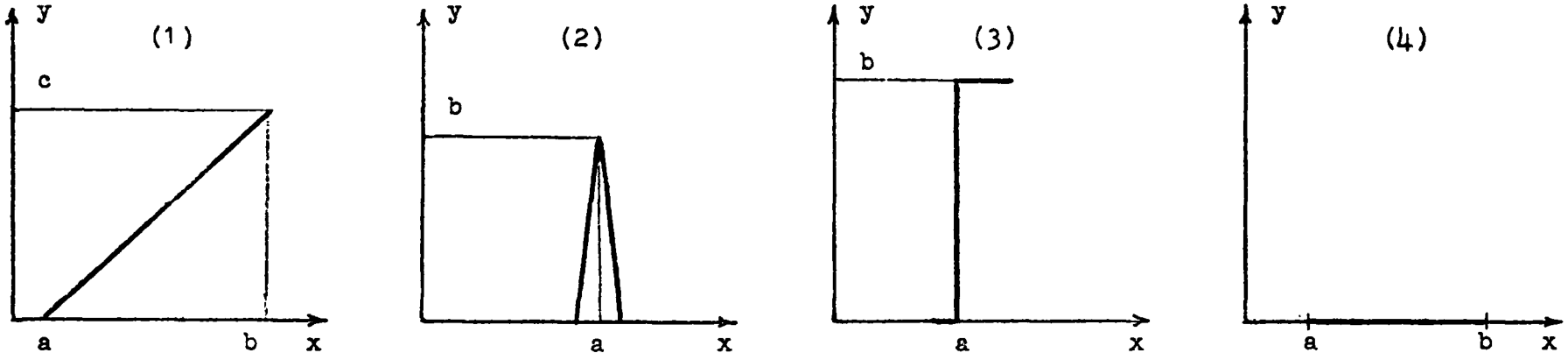

FIGURE 2

The set of parametrized basic patterns or morphs: (1) trend; (2) sudden change; (3) step function; and (4) delay function.

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